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ESTIMATING AIRCRAFT AIRFRAME TOOLING COST:

AN ALTERNATIVE TO DAPCA III

THESIS

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THESIS

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of the Air Force Institute of Technology
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Abstract

The purpose of this study was to evaluate the tooling cost estimating equation of the DAPCA III model and determine if more accurate models can be developed. The five objectives of the research were: (1) Determine the accuracy of the DAPCA III model. (2) Determine if the independent variables in DAPCA III are logically valid. (3) Determine if the data base which was used to develop DAPCA III is appropriate for estimating today's aircraft systems. (4) Determine if the accuracy of the DAPCA III model can be improved. (5) Determine if using a factor of manufacturing is sufficient to estimate tooling costs.

The study found that the accuracy of the DAPCA III model can be improved by including additional variables and updating the data base. More accurate models were developed for the data base both including and excluding the prototype aircraft systems.

When tooling was regressed against manufacturing and engineering, the data without the prototypes indicated that engineering was more significant than manufacturing. Both manufacturing and engineering were significant for the data with the prototypes.

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I. Introduction

As the United States budget deficit continues to expand, the Government has been pressured to reduce spending. Discussions both within and outside Congress have focused on reducing national defense expenditures. This attention on the defense budget has stemmed from the fact that national defense expenditures have "constituted more than three-fifths of federal consumption expenditures and a quarter of total government consumption expenditures (35:28)." When veteran's benefits and space research are also considered part of the national defense budget, "defense and related expenditures amounted to more than three-quarters of the federal consumption expenditures, or a third of total government consumption expenditures (35:28)".

With the Reagan Administration emphasis on acquiring and maintaining a strong national defense, the defense budget has doubled in six years (13:16). In the forecasted budget,

> the Pentagon's five year plan calls for accelerated spending on 15 new big-ticket weapons systems and putting at least 20 more into production. A close look at the plan shows that new systems and those scheduled for production during the next half-decade would, if they all went forward, roughly double defense procurement spending over the period [13:16].

There is also growing concern that the current level of spending on research and development will produce systems that will require large

operating and support budgets in the future. As Alexis Cain, a Defense Budget Project Analyst, stated:

> Research and development represents the acorn from which future defense budgets and force postures grow. A failure to set priorities now will lead to even more difficult choices in the future, as the expanding defense program runs up against the reality of limited resources [13:35].

If Congress does not increase defense spending or cancel new or existing weapons procurement, the Department of Defense (DoD) will be forced to take budget cuts from many programs (13:34-35). The Air Force uses program cost estimates when it makes management decisions that affect future planning and budgeting. The quality of a program cost estimate is determined by the quality of the estimates of the separate program elements. Since the cost of tooling is a significant portion of total aircraft airframe costs, it is essential that the tooling estimates be as reliable as possible. For example, the airframe tooling costs for 277 B-52 bombers and 316 F-15 fighters were $1309.9 million and $328.0 million, respectively (calendar year 1981 dollars) (12:B-81, B-176). The tooling cost is the cost to develop, acquire, and maintain the tools necessary to produce an aircraft airframe.

Aeronautical Systems Division (ASD) cost analysts are currently using parametric equations to estimate Air Force aircraft airframe tooling costs for programs in the exploratory and development stages of the acquisition cycle. Parametric models are used since program definition is normally vague during these stages. One parametric model often used within ASD is the Development and Procurement Costs of Aircraft (DAPCA) III model, which was developed by the Rand Corporation

in the 1960s and 1970s (7:15). Another technique, which is used at ASD, is to determine tooling costs based on a factor of manufacturing costs (37).

> The challenge to cost analysts concerned with military hardware is to project from the known to the unknown, to use experience on existing equipment to predict the cost of next-generation missiles, aircraft, and space vehicles [2:1].

Specific Problem

Determine some more accurate parametric models to estimate the cost of aircraft airframe tooling on new Air Force aircraft systems.

Investigative Questions

1. Is the Rand parametric model, DAPCA III, an accurate model for estimating aircraft airframe tooling costs for new aircraft systems?

2. Are the independent variables in DAPCA III logically valid?

3. Is the data base which was used to develop DAPCA III appropriate for today's aircraft systems?

4. Can the accuracy of the DAPCA III model be improved?

5. Is the alternative technique using manufacturing costs as the basis to estimate tooling costs sufficiently accurate?

II. Literature Review

Development of DAPCA

DAPCA I. In 1966, a parametric model was developed that estimated total aircraft airframe cost. The model, which later became known as DAPCA I, presented cost estimating relationships (CERs) for the following cost elements: initial and sustaining engineering, development support, flight test operations, initial and sustaining tooling, manufacturing labor, manufacturing material, and quality control (26:1). The CERs are "mathematical expressions of functional relationships between cost and weapon system characteristics (26:iii)." The authors used data on 17 post-World War II military aircraft to derive the CER for tooling (Appendix A). The tooling estimates are made in hours rather than dollars. The estimate of tooling hours can than be multiplied by either the contractor wage rate or an industry wage rate standard to determine the tooling costs. The CER developed for total tooling hours (TN) was:

$$TN = .123 \times W^{.84} \times S^{1.07} \times R^{.4} \times N^{.14} \qquad (1)$$

where

W = gross takeoff weight (lb)
S = maximum speed (kn)
R = production rate in airframes per month
N = number of airframes that have been produced [26:37]

By using standard regression analysis, the authors concluded that aircraft gross weight, maximum speed, and AMPR weight were the most significant aircraft physical and performance parameters. After further analysis of statistical indicators and sample performance, it was concluded that AMPR weight was not as significant as aircraft gross

weight; therefore, AMPR weight was not included in the final model (26:35). The aircraft gross weight was included to capture the variation in tooling hours due to the size of the airframe.

The Aeronautical Manufacturers' Planning Report's definition of AMPR weight is

> the empty weight of the airplane less (1) wheels, brakes, tires, and tubes, (2) engines, (3) starter, (4) cooling fluid, (5) rubber or nylon fuel cells, (6) instruments, (7) batteries and electrical power supply and conversion equipment, (8) electronic equipment, (9) turret mechanism and power operated gun mounts, (10) remote fire mechanism and sighting and scanning equipment, (11) air conditioning units and fluid, (12) auxiliary power plant unit and (13) trapped fuel oil [26:5].

Speed is used as an index of the structural design features of the aircraft. For example, airframes flow at higher speeds require "the use of higher cost and more difficult to work with materials, e.g., titanium, stainless steel and honeycomb sandwich structures (8:32)." This type of material is needed for an airframe "to withstand the heat generated by atmosphere at a speed of about Mach 3. . . (2:88)."

The exponent for the variable N used in equations 1 and 3 represents the hours versus quantity relationship (learning curve slope) (26:26). This learning effect is the decrease in recurring tooling costs as more units are produced. The slope of .14 was determined by finding the mean of the cumulative tooling hour slopes of 11 of the aircraft in the sample. To determine the cumulative tooling hour slope for each aircraft, the authors plotted the cumulative tooling hours versus the cumulative number of airframes produced on log-log grids. The slope was measured by visually fitting a straight line through the points. The authors reduced possible distortions in the data by using a production interval for each aircraft during which the production rate did not change and no major modifications occurred (26:26).

An adjustment factor for the rate of production (R) was included since the authors felt there was a "direct relationship between the rate at which airframes are manufactured and the physical volume of production tools that is required (26:25)." In determining the adjustment factor of R with an exponent of .4, the authors were limited to using observations on five fighter aircraft due to limited production rate data. For each aircraft system, two points, which had differing production rates, were picked on the cumulative tooling hour plot. A line was drawn using the slope of .14 to determine the respective intercept (tooling hour) values for each point. Using the intercept values and production rates of the two lines, the ratio of production rates and ratio of tooling hours were calculated and plotted for each system. An analysis of the "apparent best fit" led the authors to conclude that a factor of R with an exponent of .4 should be used to adjust the tooling hour estimates for changes in production rates (26:29).

The DAPCA I model also included a method to determine tooling provision hours (nonrecurring) and sustaining tooling hours (recurring) separately. The tooling provision hours "are the hours required to design and build production tools (26:25). "Tooling provision hours at any production rate (TR):

$$TR = .123 \times W^{.84} \times S^{1.07} \times R^{.4} \tag{2}$$

where

W = gross takeoff weight (lb)
S = maximum speed (kn)
R = production rate in airframes per month [26:37]

The sustaining tooling hours "are the hours required to maintain tools and provide related services in the course of production (26:25)."

Sustaining tooling hours (TS):

$$TS = TN - TR = TR(N^{.14} - 1) \qquad (3)$$

where

TN = total tooling hours
TR = tooling provision hours at any production rate
N = number of airframes that have been produced [26:37]

DAPCA II. The Rand Corporation updated the DAPCA I model in 1972. The new model, DAPCA II, was based on a revision of the DAPCA I data base. The new tooling CER was developed using data on 29 aircraft systems (Appendix A). Using regression analysis, the authors found AMPR weight, maximum speed, quantity, and production rate were the most significant explanatory variables to estimate tooling hours (27:15). The CER developed to estimate total tooling hours (T) was:

$$T = 4.0127 \times A^{.764} \times S^{.899} \times Q^{.178} \times R^{.066} \qquad (4)$$

where

A = AMPR weight (lb)
S = maximum speed (kn) at best altitude
Q = cumulative quantity including flight test airframes
R = production rate, deliveries per month [27:15]

The major differences between DAPCA I and II are due to the updated data base, the change from gross takeoff weight to AMPR weight, and no differentiation between recurring and nonrecurring tooling hours. Dropping the gross weight eliminated the problem of defining gross weight consistently. Gross weight varies based on mission requirements. "Gross take-off weight is a function of the amount of avionics installed, type and amount of armament, and fuel load (4:27)." AMPR weight was used to indicate the relationship between the size of the aircraft and tooling hours (27:15).

DAPCA II does not provide separate estimates for nonrecurring and recurring tooling, since "definitional inconsistencies among contractors made the distinction meaningless (23:11)."

Another major change was the way the learning curve effect was incorporated into the model. Quantity was included as one of the independent variables when regression analysis was used to develop the CER. The exponent for the quantity variable indicates a measure of the learning curve slope. Production rate was also used as an independent variable. The methodology used in DAPCA I to calculate a production rate adjustment factor was not used in DAPCA II because of data limitations (27:15-16).

A later study by the Rand Corporation addressed the "degree of confidence that can be placed in cost predictions for airframes obtained from" DAPCA II (36:1). The authors determined prediction intervals for five design points with weight and speed values that generally bound the aircraft in the sample. "Prediction intervals are limits within which, with a specified probability, the value of a single future observation lies (36:2)."

The study revealed wide prediction intervals for total aircraft airframe costs using DAPCA II. At a 95 percent confidence level, "the actual cost will lie some where between a 43 percent underrun and a 75 percent overrun (36:30)." The authors emphasized that when a parametric model is used to establish cost figures for a system acquisition, the width of the prediction interval is extremely important. Since the analysis of the prediction intervals in the study were for total aircraft airframe costs, the prediction intervals for total tooling hours is

unknown. However, the study implies that DAPCA II tooling estimates may have wide prediction intervals.

DAPCA III. In 1976, the DAPCA model was again updated. The data base was modified to include only those aircraft systems which seemed relevant to the systems that were current at that time. The 25 aircraft systems used to develop the aircraft airframe tooling CER are listed in Appendix A. The CER for total tooling hours (T) was:

$$T = 522.39 \times A^{.6214} \times S^{.5323} \times 200^{-(b+1)} \times Q^{b+1} \times 10^{-6} \tag{5}$$

where

A = AMPR weight (lb)
S = maximum speed at best altitude (kn)
Q = cumulative airframe quantity
b = -.811 (exponent corresponding to cumulative average learning curve slope .57)
b+1 = .189 [7:15]

The total tooling hours were plotted against aircraft quantity for each aircraft used in the sample. The tooling hours for quantities 25, 50, 100, and 200 were regressed against AMPR weight and speed. Since the cumulative curves appeared to be linear after quantity 20, quantity 200 was used as the point to obtain tooling hours.

An average aircraft tooling hour slope was used to adjust for the learning curve effect. An average slope of .57 was calculated. The exponent, b (-.811), was determined by dividing the log .57 by the log 2. Since the cumulative average curve has a coefficient of b, the cumulative total curve has a coefficient of b + 1. To adjust the tooling hour estimate for quantity 200, a factor of 200 with an exponent of b + 1 was used in the CER. The cumulative quantity, Q, with an exponent of b + 1 was used to adjust the tooling hour estimate for the learning curve effect (7:9-10).

Boren found that including a production rate variable did not reduce the residuals and was not significantly statistically (23:12). Therefore, the DAPCA III model did not include a production rate variable.

Since there were significant average deviations from the regression line for small quantities, the total tooling estimate was adjusted for quantities less than 20:

$$T\ (\text{adjusted}) = T \times .1232 \times Q^{.699} \quad [7:15] \tag{6}$$

The adjustment factors were calculated by assuming that a quantity of 20 units will have tooling cost five times that of a quantity of two units. The derivatives of a and b proceeds as follows:

$$1.00 = a \times 20^{b} \tag{7}$$

$$.20 = a \times 2^{b}$$

$$5 = 10^{b}$$

Solving for the unknowns, Boren determined that b = .6990 and a = .1232. Boren emphasized that this approach for adjusting for smaller quantities provides a rough approximation. He recommends that DAPCA III not be used on programs that have a very small production quantity.

DAPCA Critique

A 1977 Rand study evaluated several parametric models available to estimate aircraft airframe costs. The authors concluded that "parametric cost models requiring only a few aircraft characteristics as inputs can provide useful estimates of airframe cost (23:47)." However, the authors were concerned that the models in some instances "also produce estimates that may be off-target by over 100 percent (23:47)." To

improve future models, the following recommendations were made:

a. Provide a way to distinguish between Air Force and Navy aircraft program costs.

b. Determine an objective procedure to measure technological change.

c. Use dummy variables to distinguish between types of aircraft: cargo, bomber, and fighter.

d. Investigate contractor variables (23:48).

An evolution of parametric cost models was presented in a 1981 Rand study. The study pointed out that:

> Physical and performance factors such as weight and speed are not sufficient in themselves to deal with next generation aircraft, but some judgmental factors are too unreliable to include in a parametric cost model [22:20].

The tooling costs estimated by DAPCA III are based on weight and speed. Therefore, there is reason to doubt that DAPCA III is the most valid parametric model for estimating the cost of aircraft airframe tooling on new Air Force aircraft systems.

<u>Other Related Studies</u>

The following review of several studies on aircraft airframe cost estimating will provide insight into potential cost relationships and modeling techniques.

In April 1967, The Planning Research Corporation (PRC) published an airframe model which consisted of separate estimating equations for several cost elements at production units 10, 30, 100, and 300. Cost-quantity curves were derived from these estimates (3:10). Since high performance aircraft have a high proportion of nonrecurring cost and therefore extremely steep slopes, PRC felt the cost curves for

engineering and tooling might not be linear. It was determined that the CERs for engineering and tooling would be more feasible if recurring and nonrecurring costs were separated (33:I-3, II-7). When PRC tried to separate these costs, variability was introduced which was not explained by the CER. PRC found that by combining the engineering and tooling costs and developing CERs for nonrecurring and recurring costs, the variability could be significantly reduced (33:I-4).

The nonrecurring tooling and engineering CER had two independent variables:

a. the ratio: (empty weight minus airframe unit weight) divided by airframe unit weight.

b. maximum speed at altitude in Mach number.

The independent variables in the recurring tooling and engineering CER were:

a. the ratio: (empty weight minus airframe unit weight) divided by airframe unit weight.

b. maximum speed at altitude in Mach number.

c. percent change in airframe weight from unit one at the nth production unit.

d. calendar year of first delivery minus 1940 (33:III-17, 20, 21).

The time variable was "used to express the effect of time-related factors, such as changes in the technological state-of-the-art (33:II-2)."

The PRC model requires inputs that are "not available until a production schedule has been laid out and a contractor chosen (23:19)." Therefore, it cannot be used to estimate programs early in the

acquisition cycle. Also, since the estimates for tooling and engineering are combined, estimates for tooling costs are not available.

J. Watson Noah Associates, Inc. developed CERs in 1973 for recurring and nonrecurring total aircraft airframe costs. The authors estimated cumulative cost-per-pound of AMPR weight at quantity 100, and then applied a learning curve with an 80 percent slope (29:56).

The independent variable used in the nonrecurring total airframe CER were:

a. maximum speed at best altitude.

b. gross take-off weight divided by AMPR weight.

c. complexity indicator variable.

d. technological index.

The recurring total airframe CER had the following independent variables:

a. maximum speed at best altitude.

b. AMPR weight.

c. complexity indicator variable.

d. technological index (29:50).

The complexity indicator variable, which is based purely on a judgment call, was used to capture differences in complexity. The authors found four aircraft whose costs were seriously underestimated. "Each had a major mission or performance parameter which required significantly new and complex technology (29:48)."

The authors felt that an appropriate measure of technology should be "constructed on the basis of the model changes that have occurred over an appropriate period of time (29:29)." Therefore, the technology progress

index was based on the "number of model changes that have occurred since aviation progress began to accelerate during World War I (23:29)."

In 1977, J. Watson Noah Associates, Inc. revised their 1973 model. The 1977 model consisted of two CERs. One estimated the total aircraft airframe costs for design. The other estimated the total aircraft airframe costs for production. Both recurring and nonrecurring tooling costs are included in the production CER (23:34). The authors also used a log-linear form in the 1977 model, while the 1973 model used an arithmetic functional form (4:17) Again, the tooling cost estimates are not available since the CERs estimated total aircraft airframe costs.

The Rand Corporation performed a study in 1976 to determine if there were characteristics in addition to weight and speed (the independent variables in DAPCA III) "that would make an estimating model more flexible and hence better able to deal with characteristics peculiar to individual aircraft (24:v)." The authors developed a total aircraft airframe model. The CER estimated the total cost for 100 units as a function of airframe unit weight and maximum speed (24:42). All attempts to increase the reliability of the estimates by using additional independent variables were not productive (24:53).

In 1977, the Rand Corporation developed a fighter aircraft estimating model. The data, which was from the DAPCA III data base, included attack and fighter aircraft, plus B-58, T-38, F-84, F-86A, F-89, F-3D, and F-101. The authors developed a model specifically to estimate fighter aircraft airframe costs, since they felt that such a model would provide a better estimate of fighter aircraft cost than from a model

derived from a sample including the KC-135 tanker and the C-5 cargo aircraft (21:1). The independent variables in the model were:

a. airframe unit weight.

b. maximum speed.

c. gross take-off weight divided by airframe unit weight.

d. specific power, which equals:

$$\frac{\text{(static thrust)} \times \text{(max speed)}}{\text{combat weight}} \times (.003069) \qquad (8)$$

[21:2, 6]

This model also calculated total airframe costs, so an estimate of only tooling cost is not be available. The estimates from the all-fighter sample model were compared to estimates from a broader-based model. The authors found "that when estimating total cost it makes little difference which of the models is used (21:14)." Although the authors were not able to show a fighter model was better than a broader-based model, this does not mean it could not be true.

The Modular Life Cycle Cost Model (MLCCM) was developed by the Grumman Aerospace Corporation in 1976 and later updated in 1980. The model estimates airframe, engine, and avionics costs in the Research, Development, Test, and Evaluation (RDT&E), Production and Operation and Support (O&S) phases. MLCCM is comprised of CERs which "were developed to conform to a work breakdown structure format to provide visibility to the subsystems in each design (19:30)." The independent variables for the total tooling labor manhours were:

a. the number of prototype aircraft in first buy.

b. ultimate load factor, which is the amount of "g" forces the aircraft can sustain.

c. maximum Mach number.

d. total wetted area, which is a measure of aircraft volume (3:20).

The MLCCM model uses an index to adjust the cost of all-aluminum airframe estimates for differences in the amount of composite materials. The cost factors are developed for each of the main sections of an aircraft, wing, fuselage/nacelle, and tail (19:32).

Clemson University performed a series of studies in the late 1970's and early 1980's to determine an econometric model to estimate the cost of military aircraft airframes. "An econometric model is a system of interdependent equations that describe some real phenomenon . . . These equations are solved simultaneously to find the values for unknown variables . . . (9:273)." The Clemson model determines the cost to produce an individual aircraft based on its start date and its planned delivery date. Another feature of the model are four production cost drivers: " *learning by doing*, learning over time, the speed of the production line, and production line length (40:iv)." The equations in the model incorporate the technical features of the airframe production program and the contractor's behavior (40:iv).

The model has the advantage of providing decision makers with the effects of alternative schedules (40:226). The authors note that the model "requires considerable knowledge of both the planning and production stages in any airframe program (40:2)." This information is not available in the early stages of planning. Also, the model does not provide a breakout of costs by cost element, so the cost of tooling is not attainable.

In 1982, the Air Force Institute of Technology sponsored a thesis to determine if there was justification to support the development of separate cost equations for the airframes of fighters, attack, and cargo

aircraft. A statistical procedure, factor analysis, was performed on performance characteristics of the aircraft airframes. The authors concluded that the factor analysis justified separating the airframe cost data by fighter, attack, and cargo aircraft and developing a separate CER for each group (3:86).

A thesis on estimating the cost of composite material airframes was completed at the Air Force Institute of Technology in 1983. The author developed an index of adjustment factors that reflect the differences between aluminum and composite material airframe costs for nonrecurring tooling manhours, recurring manufacturing manhours, and material dollar costs. The tooling costs were estimated by comparing tooling hours generated by the ICAM Manufacturing Cost/Design Guide to set up hours used in the Fabrication Cost Estimating Technique (FACET)(19:41,42). There is a potential problem, since the tooling costs captured by the two models are not identical. The author warns that "uncertainties in the exact relationship between the tooling cost captured in FACET and the tooling costs captured in the ICAM manual must be resolved before the index can be used (19:93).

An aircraft airframe cost model, which has adjustment factors to account for changes in technology and variations in the material composition of the airframe, was developed by the Aeronautical Systems Division in 1984. The DAPCA III CERs are used in the model. An equivalent metals weight factor is determined based on the percentages of each type of material in the airframe. The weight independent variable to be used in the DAPCA III model is adjusted using this weight factor (6:8-11). An estimate of the tooling costs is calculated using DAPCA

III. This estimate is then adjusted using a technology factor, which is determined by the judgment of experts.

Summary

There have been several models developed to estimate the cost of aircraft airframe tooling. The DAPCA III model is often used at the Aeronautical Systems Division. The purpose of this study will be to evaluate the accuracy of the tooling cost estimating equation in DAPCA III and determine if models can be developed that are more accurate than the DAPCA III.

III. Methodology

Accuracy of DAPCA III

To determine whether the DAPCA III model is an accurate estimator of aircraft airframe tooling cost estimates, DAPCA III will be tested using actual aircraft specifications from the Air Force Cost Center's Cost Estimating System (CES)(10:4-1 thru 4-923). These specifications will be used in Eq (5) to determine a DAPCA III estimate. The aircraft systems used for this test will be the systems used by Rand to develop DAPCA III. The estimates derived from running the model will be compared to actual tooling costs in the CES. To determine the representative difference between the actual costs and the estimated costs the following formula will be used:

$$\text{representative difference} = \sqrt{\frac{\sum(\text{actual-estimate})^2}{\text{number of observations}}} \qquad (9)$$

The representative difference will be calculated for the data base without prototypes and with prototypes. The representative difference is used to determine the accuracy of DAPCA III, since it can be compared to the coefficient of variation or root mean square of the models which will be developed during this research.

DAPCA III Independent Variables

An analysis of previous studies will provide insight into whether the independent variables used in DAPCA III are logical. Each independent variable will be discussed and a conclusion made whether it it is still a logical variable for estimating costs of future aircraft systems.

DAPCA III Data Base

The aircraft systems in the CES will be reviewed to determine which aircraft systems provide the best representative sample of future aircraft systems. The data base used to develop DAPCA III will be compared to the aircraft systems identified in the CES.

Alternative Models

Considering the results of the analysis of independent variables and the data base, a model which estimates aircraft airframe tooling cost on new Air Force aircraft systems will be developed. To identify the independent variables for the model, the systems attributes that are felt to have an effect on the cost of tooling will be determined. Then the aircraft physical and performance characteristics that reflect those system attributes will be identified. These characteristics will then be considered as potential independent variables. Possible indicator variables and interaction effects will also be considered. The indicator variables, which are also known as dummy variables, will be used as a way of "quantitatively identifying the classes of a qualitative variable (28:329)." Interaction effects on the dependent variable Y occur when, given independent variables X1 and X2, "both the effect of X1 for a given level of X2 and the effect of X2 for a given level of X1 depends on the level of the other independent variable (28:232)."

After the potential independent variables are identified, the impact each variable has on tooling costs will be specified. For example, if weight is chosen as an independent variable, it would be specified whether an increase in weight would be expected to increase or decrease the cost of tooling.

All analyses to determine an alternative model to DAPCA III will be performed on two separate data bases. One data base will include data on the prototype aircraft systems. The other data base will eliminate the data on the prototype aircraft systems. This procedure will provide information on the impact of the developmental aircraft systems on the total cost of tooling. The criteria to identify the prototype aircraft in the data base will be:

a. Identify any aircraft which have a prototype model designator. For example, the A4D-1 prototype was designated XA4D-1.

b. If the number of prototypes is known and the first lot of an aircraft is that number, assume the first lot contains the prototype data.

c. If first lot is large, assume prototype data is included as part of the first lot.

Since the cost of direct labor varies between contractors, the dependent variable in the models will be in direct labor hours instead of dollars.

The method to capture the learning curve effect will be similar to the method used in DAPCA III. The major difference will be the dependent variable which will be the cumulative average tooling hours through unit 100, while DAPCA III used the cumulative average tooling hours through unit 200. By using only the first 100 aircraft, possible distortions due to major modifications are minimized. The cumulative average tooling hours through unit 100 for each system will be calculated by using the following formula:

$$CA_{100} = A \times 100 \qquad (10)$$

where

CA_{100} = cumulative average tooling hours for units 1 through 100
A = first unit cost (hours)
b = rate of learning (20:18)

To determine the rate of learning and the first unit cost (hours) the lot data in the CES report will be used in the cumulative average learning curve software program developed by Hutchison in 1985 (18:26-69). The median of the learning curve slopes for each data set will be used as the average learning curve slope for that data set. The learning curve slope in DAPCA III was determined using the arithmetic mean. The median is a better measure of the average learning curve slope than the arithmetic mean, since it does not distort the average when the data is skewed to the left or right. Also, an abnormal learning curve (e.g. a positive slope) would not raise the median slope as much as it would raise the arithmetic mean slope.

The cumulative average tooling hours through unit 100 will be regressed against the independent variables using the statistical package on the SAS program (34:113-137, 655-709). The data will be regressed in both linear and log-linear forms to determine which formulation has a lower predicting error. The data will also be regressed with and without inclusion of the prototypes in the data set, to determine if there is a difference in predicting tooling hourss dependent on the stage of development.

Initially, the data will be regressed using a multiplicative relationship, where Y is A times X to the B power. This relationship "implies a deceleration or an acceleration in cost depending on the

values of the coefficients of the logarithmic terms (15:4)." The logarithm-linear (multiplicative) form has been "used by Rand because of the implied diminishing marginal returns when coefficients are less than 1.0 (4:14)." DAPCA III is in logarithm-linear form. Rand found this form to fit the data best.

The multiplicative form must be changed to a linear form so that regressions calculations can be performed. The transformation will be done by taking the natural logarithms of both sides of the equation ($\ln Y = \ln A + B \ln X + \ln e$).

The data will also be regressed using a standard-linear relationship ($Y = A + BX + e$). This linear form implies a constant relationship between the dependent and independent variables (15:4). The results of the linear model will be compared to the results of the logarithm-linear model to determine which form fits the data best.

To determine whether the model is linear or log-linear, the models for the data both with and without the prototypes will be evaluated using the following criteria:

a. Calculated F-ratio greater the critical F-value at a 90 percent confidence level. If the F test statistic is significant, then there is a relationship between the dependent variable and the set of independent variables (28:289).

b. Calculated t-statistic greater than the critical t-statistic at an 85 percent confidence level for each independent variable in the model. If the t statistic is significant, then the amount of variation in the dependent variable that is explained by the independent variable is significant (28:289).

c. For linear models, a low coefficient of variation (11:54).

d. For log-linear models, a low root mean square error(11:7).

e. For the logarithm-linear form, if the parameter estimate (coefficient) is greater than 1.0, then as X increases, Y increases more than proportionally (exponentially), which means the independent variable is questionable in this relationship.

The models that appear to have the best fit will be analyzed for potential outlying observations in the data set. To determine if any observations are extreme with respect to X, the leverage values will be reviewed. The leverage value is the measure of the distance between the X values for a specific observation and the means of the X values for all observations in the data set (28:402). A leverage value greater than 2p/n, where p = number of parameters and n = number of observations, will indicate outlying observations with respect to X (28:403).

The studentized deleted residuals will be reviewed to determine if any of the observations in the data set are outlying with respect to Y (28:404). If the studentized residual is greater than the t-value at a confidence level of 90 percent, they will be considered outlying observations with respect to Y.

The Cook's distance measure will be used to determine the impact of each observation on the estimated regression coefficients (28:407). If the Cook's d for an observation is greater than an F-value at 50 percent, that observation will be considered an influential observation.

The learning curve effect will be integrated into the models that are selected. Since the models will estimate the cumulative average tooling hours of the first 100 aircraft, an adjustment for varying quantities of aircraft and the learning effect must be made. If the models are logarithm-linear, the following adjustments will be made:

If selected model is Y = AX(exp b1), then adjusted model will be:

$$Y = A \times X^{b1} \times Q^{(b2 + 1)} \times 100^{-(b2 + 1)} \qquad (11)$$

where

Y = cumulative average tooling hours
A = intercept
X = independent variable
$b1$ = coefficient of independent variable
Q = quantity
$b2$ = average learning curve

This methodology is analogous to that used for DAPCA III, Eq (5). If the models are standard-linear, the following adjustments must be made by the the user of the model:

If selected model is Y = A + b1X, then using the average learning curve slope and the cumulative average hours of the first 100 airframes determine the cost of airframe one. Use the estimate of the first unit hours (A) in the following formula:

$$Y_X = AX^b \qquad (12)$$

where

Y_X = cumulative average tooling hours of first X airframes
A = first unit cost (hours)
X = cumulative number of airframes
b = rate of learning

The cumulative average number of hours is the multiplied by the number of airframes to determine the total cumulative hours.

The coefficient of variation/root mean square for each of the models selected will be compared to the value of the representative difference for the DAPCA III model. This comparison will identify which model is more accurate based on the results of the analysis.

Alternative to Manufacturing Factor

The total cumulative tooling hours of the aircraft systems used to develop the cumulative average tooling hours in the previous section will be regressed against the engineering and manufacturing total cumulative hours to determine if there is a relationship between tooling and engineering or manufacturing hours. A model will be developed for the data base with prototypes and without prototypes. To determine if this relationship also existed in the past, a historical simulation will be performed. With historical simulation the data for most recent aircraft systems are removed from the data base and then regression analysis is performed on the reduced sample. The estimates from the reduced-sample model are compared to the actual data (5:55). If the data base has a small number of observations, an equivalent number of older aircraft systems will be added to the data base when the most current systems are removed.

IV. Analysis

Accuracy of DAPCA III

The inputs for the DAPCA III model were obtained from the Air Force Cost Center's CES (Appendix B). Two data points were not available in the CES. The first, the B-52 AMPR weight, was taken from the Rand report on DAPCA I (26:7). The second, the C-130 AMPR weight, was obtained from information in the Lockheed Aircraft Corporation Report ER 2342 (31:7-12).

The tooling estimates from DAPCA III were compared to the actual tooling hours reported in the CES. The representative difference for the data without prototypes was the square root of (679,165,399.3 hours/25) or 5212.16 hours (Appendix C). The average tooling hours were 210,176 hours/25 or 8407.04 hours. Therefore, the representative difference percentage was 5212.16/8407.04 or 62.00 percent. The representative difference for the data including the prototypes was the square root of (669,863,341.6/25) or 5176.34 (Appendix D). The average tooling hours were 236,909 hours/25 or 9476.36. Therefore, the representative difference percentage was 5176.34/9476.36 or 54.62 percent.

DAPCA III Independent Variables

Size. DAPCA III uses airframe unit weight to explain the variability due to the size of the airframe. Weight is "a logical variable because it is an index of size, and all other things being equal a large aircraft should cost more than a small one (24:12)." The airframe unit weight was also found to be a significant variable in the Noah, 1976 Rand, and 1977 Rand Fighter models.

Gross takeoff weight and the ratio of gross takeoff weight to airframe unit weight have been considered as possible independent variables in some models. Large warned there is a problem with "achieving a consistent definition of gross takeoff weight (24:24)." As Bennett explained,

> gross take-off weight is a function of the amount of avionics installed, type and amount of armament, and fuel load. This results in different values of gross weight depending upon the mission requirements for which it is defined [4:27].

With this in mind, gross takeoff weight should not be used to capture the impact of size on cost.

The PRC model used the ratio (R) of empty weight minus airframe unit weight to airframe unit weight. Large cautioned that "R is only a proxy for weight and not a good one. Two aircraft with much the same empty weight . . . can have very different Rs. . . (23:21-22)."

Carrier emphasized that when using a weight-cost relationship

> for estimating purposes it is important to make sure the construction and materials of the airframe to be estimated are similar to those of the airframes on which the cost estimating relationship is based [8:3].

There has been a growing concern that the increased use of composites in aircraft airframes will make estimating with the existing data base questionable. The data consists of primarily aluminum aircraft airframes. "There are less than 10 aircraft in the inventory with significant quantities of composite materials (19:5)." In most of these aircraft the composite material is less than 15 percent of the airframe weight. "Using regression analysis of a data set with just these aircraft in it to make cost predictions about composite airframes

would not provide results that could be used with any degree of confidence (19:5)."

This same concern impacts the estimates of airframes which are partly composed of steel and/or titanium. "Titanium is much more expensive than aluminum and is more difficult to fabricate (24:3)."

Today's airframe cost estimates must address the issue of variations in structural materials to ensure reliable estimates. Since regression analysis is not an appropriate technique, the application of an adjustment factor, such as the one developed by ASD, seems the best approach.

Although surface area was not used in the DAPCA III model, it seems to be a logical independent variable. A variable such as airframe surface area or wing area should capture the variations in size.

While weight has explained the variations in cost due to size, it does not capture the cost variability caused by performance differences. As Carrier explained,

> The weight and general purpose of two items, for example, might be exactly the same, yet the performance of one, gained through advancement in design, materials, and fabrication techniques, might be considerably better than that of the other. The possibility exists, therefore, that the improved item might cost considerably more, and if its cost is estimated on the basis of weight alone it might be underestimated by a large amount [8:3,5].

Performance. One performance characteristic that tends to vary with tooling costs is speed. The DAPCA III, PRC, Noah, 1976 Rand, 1977 Rand Fighter, and MLCCM models all used speed as an independent variable. Large cautions that "other organizations have found it to be of no significance (24:12)."

DAPCA III does not include any independent variables that would capture the variations in maneuverability of the aircraft systems. Variations in maneuverability would change the degree of stress on the airframe and could vary the structural and tooling requirements. Two characteristics which logically represent the aircraft's maneuverability are the thrust-to-weight ratio and the rate of climb. Since climb rate is based on gross takeoff weight it should not be used for the reasons mentioned earlier.

Production Rate. DAPCA III does not consider changes in the production rate. The authors of DAPCA I believed that there "is an obvious direct relationship between the rate at which airframes are manufactured and the physical volume of production tools that is required (26:25)." Carrier also felt production rate impacts tooling costs. He stated that "the expected number of components to be produced helps determine the production rate which in turn has an effect on tooling costs and on production costs through the amount and type of tooling . . . (8:3)." He further explained,

> An extremely low production rate is held to be inefficient because of under-utilization of facilities. Up to a certain point output can be increased without a proportional increase in the cost of management, tooling and facilities. Beyond that point these costs increase more rapidly than output, offsetting the economies of scale secured in other aspects of production [8:56].

Dreyfuss also agrees that some tooling is time-dependent:

> an initial set of tools is fabricated to support manufacturing at some specified maximum rate of production (e.g., four aircraft per month). Recurring or sustaining tooling has a fixed component that is time-dependent and a variable component that is a function of quality. The former will increase as program length increases; the latter is largely unaffected by production rate [14:8].

However, he also explains that it is difficult is not impossible to isolate the portion that is time-dependent. He concludes that "within the limits of the rates examined production rate has little effect on tooling hours (14:39)."

In 1974, the Rand Corporation published a relatively thorough study, which analyzed "the effect of production rate on the cost of selected types of military hardware (25:v)." The authors concluded that their analyses "suggest but do not confirm that cumulative tooling cost is not highly sensitive to the rate of output (25:20)." They explained:

> In general it appears that an increase in production rate should result in a decrease in such costs, but in any specific case the effect depends on how rate changes are achieved, the availability of suppliers, the local labor supply, management policy, the timing of rate changes, plant capacity, plant backlog, and a number of other factors [25:v].

In 1980, Womer noted that the Rand reports on aircraft cost, which "have been cross-sectional studies characterized by a few observations on many aircraft programs," credit "production rate with little, if any explanatory ability (39:2)." He also noted that some time series studies on single airframe programs "indicate that production rate is correlated with costs on a program (39:2)." There does not seem to be any consistent relationship between production rate and tooling costs. Womer reported there are "documented cases where increases in production rate have been associated with increases, decreases, and no change in the unit cost of production (39:1)".

Since production rate is hard to predict in advance, may be subject to change, and its affects are dependent on how the rate is

achieved, production rate should not be considered as a possible independent variable.

Learning Curve. DAPCA III includes an adjustment to the estimate for the effect of learning. Since production efficiency improves with greater production, it seems logical that the influence of learning should be incorporated into the model.

Technology. DAPCA III does not include an independent variable for changes in technology. However, some studies have reported that increases in manufacturing technology impact the cost of tooling.

> Clearly, technological progress has had a significant effect on cost reduction, and by itself has reduced the costs of tactical aircraft on average about 3.3 percent per year [16:27].

There has been little agreement on how to incorporate the affects of technological advances into airframe CERs. As the authors of the Noah model point out, " there is no directly measurable physical quality that would tell us the level of manufacturing technology embodied in a given aircraft model (29:29)."

The PRC model used the year of first production delivery as a proxy technological variable (T). "The time variable, T, becomes less important each year because the input is in logarithmic form (23:23)." This approach has been criticized, because "early estimates can be off by several years (24:10)." Hildebrandt explained that using "time to represent technological progress ignores the differences in production know-how among firms and assumes that they share a technology (16:9)".

The technological index in the Noah model is based on the number of model changes that have occurred since World War I. The authors felt their approach is more appealing since it "results in a relatively slower rate of increase in the technology index during wartime and a

more rapid increase during the post-war period as the number of new models and prototypes increase (29:32)." Large warns that "certain incongruities result from this method; e.g., the B-47 and C-124 have the same index number, although the former is a much more advanced airplane (23:29)." He also cautions that since the "number of new models of fighter aircraft is unlikely to change much from year to year, it functions essentially as a constant (23:31)."

Another alternative to measure the technological advances is to develop a subjective factor. This approach has been used at ASD in their aircraft airframe cost model. Large cautioned that subjective factors are "questionable because a priori judgments are often different from ex post facto judgments (24:10)."

For early planning studies, the required technology may not be defined. The manufacturing technology for a system is determined during product design, which is often performed after early planning studies. Since detailed information will probably not be available it is difficult to identify an independent variable to capture technological changes.

Complexity. DAPCA *III* does not have an independent variable for complexity. The Noah model used a subjective factor to explain the variability resulting from complexity differences. The Noah model estimates

> are contingent upon the ability to choose the proper complexity factor ahead of time rather than after the fact, and several informal tests at Rand have shown that engineers can disagree about an aircraft program's difficulty [23:46].

Large reported that even when the aircraft program's difficulty was agreed to, "incorporating a subjective index of difficulty improves some estimates but degrades others (24:53)."

Recurring/Nonrecurring. The DAPCA III model estimates total tooling costs. Some models have separate CERs for nonrecurring and recurring costs. Unfortunately, there is not an established industry-wide definition of nonrecurring costs. The authors of the PRC model used experience and judgment to separate recurring and nonrecurring costs (33:II-15). For the Noah model an empirical method was used to separate costs; however, the authors noted that their method for separating costs may place costs in the nonrecurring category for effort that was not defined as nonrecurring (29:24).

Aggregate versus Cost Element. DAPCA III provides cost estimates at the cost element level. There has been some discussion as to whether a more accurate estimate can be attained by estimating total program cost (aggregate) rather than individual estimates for the cost elements. Those analysts that feel estimates should be at the aggregate level believe that the contractor cost data is not consistent at the cost element level.

> What one company calls engineering another company calls tooling, or a given company will change definitions to conform to cost-accounting standards, and it has never ben possible to adjust the data to eliminate all discrepancies [22:18].

A Rand study found that neither estimating at the cost account or aggregate level has significantly greater accuracy (17:2). Large reported that estimating at the aggregate level was "less useful because of the lack of detail . . . (24:53)." Therefore, developing a separate model for tooling costs should not impact the accuracy of the estimate.

Indicator Variables. In a February 1976 Rand study several indicator variables were analyzed. "In the course of the study

aircraft were stratified by type (fighter, bomber, cargo), age, speed, weight, weight and speed, and structure design load factor (24:12)." The only category which seemed appropriate for an indicator variable was cargo aircraft. The cargo aircraft were analyzed by using an indicator variable and by treating the aircraft as a separate sample. The authors concluded that "there is no persuasive reason to consider cargo aircraft as a distinct group in so far as tooling is concerned (24:122,124)." Another point emphasized by the authors was that the sample size of each aircraft type was too small "and probably always will be, because at some point it becomes clear that experience with old aircraft is no longer relevant (24:12)."

The PRC model used an indicator variable in the nonrecurring engineering and tooling equation for prototype and concurrent development programs. An indicator variable was also used for Navy and Air Force development programs. Bennett also felt that an indicator variable was necessary for Navy and Air Force programs to show the "effect on cost of different service imposed requirements for the same aircraft (4:27)." Indicator variables for Navy and Air Force programs seems appropriate.

Using indicator variables for aircraft type can have some limitations.

> For example, the B-1B is as fast as a fighter but weighs as much as a bomber. Neither a data base of fighters or one of bombers could produce a reasonable estimate, but together, the speed of the fighters and the weight of the bombers and cargo aircraft combine to produce a better estimate [19:25].

To avoid this type of limitation, it seems appropriate to evaluate the independent variables in the model to determine if there are any observations which do not fit the assumptions of any of the indicators.

DAPCA III Data Base

The DAPCA III data base, which is listed in Appendix A, has several aircraft systems which were developed and produced in the 1950s and the early 1960s. Since 1976, when DAPCA III was published, there have been aircraft entered into the inventory. By excluding the earlier models and including the more recent models, a data base which better represents the future aircraft systems was obtained (Appendix E).

Alternative Models

Independent Variables. Based on the analysis of the independent variables used in DAPCA III, the system attributes which are known to have an effect on the cost of tooling are size, performance, and maneuverability of the aircraft. The aircraft physical and performance chararteristics which will be considered as potential independent variables to reflect the system attributes were:

a. Size.

1. Airframe Unit Weight (AUW): "average airframe unit weight (lbs) for the first 100 production aircraft (10:4-2)."

2. Wing Area (WA): "maximum wing area in feet (10:4-4)."

b. Performance.

1. Maximum Speed at Altitude (S): "maximum mission speed at altitude in knots (10:4-3)."

c. Maneuverability.

1. Thrust to Weight Ration (TWR): military (intermediate) static thrust of the engine at sea level in pounds divided by aircraft unit weight (10:4-3).

Based on the author's judgement, it was concluded that there is no interaction affect between these potential independent variables.

Since past studies have determined that using an indicator variable to differentiate between Navy and Air Force programs have improved the estimating value of the models, an indicator variable for this qualitative variable was tested in the models. Navy programs were designated as the baseline and given the value of zero. Air Force programs were given the value of one. The indicator variable was combined with the other independent variables to determine if there was any significant interaction effect. The results are reported with the model analysis below.

An indicator variable was also used to quantify a qualititive variable which places cargo and bomber aircraft in a different category than fighter, attack, and trainer aircraft. Cargo and bomber aircraft were given the value of one, and fighter, attack, and trainer aircraft were given the value of zero. This indicator variable was also combined with the other independent variables to determine if there was any significant interaction effect. The results are reported with the model analysis below.

Specification of Independent Variables. The independent variables are expected to influence the amount of tooling for the aircraft airframes in the following ways:

a. An increase in in the size of the aircraft (aircraft unit weight or wing area) will result in an increase in the amount of tooling needed.

c. An increase in the performance of the aircraft (maximum speed at altitude) will result in an increase in the amount of tooling

needed. This is due to the increased demands that will be placed on the structure of the airframe.

d. An increase in the maneuverability (thrust to weight ratio) will result in an increase in the amount of tooling needed. This also places increased demands on the airframe structure.

CES Data Base. The CES data for the independent variables is listed in Appendix F. The aircraft unit weight, and thrust for the B-1 were not in the CES and were obtained from separate Rockwell International reports (1 and 3). The data for each aircraft system was reviewed to determine which lots would be used for the analysis. The tooling hours are in thousands. Since the data is proprietary it is not listed in this document. For those readers that have access to the CES a listing of the lots that were used is in Appendix E. When available, the first model of each aircraft system was used. For some models the cost data was not in the CES, so a later model was selected. A description of the lot data for the prototypes for each aircraft wywtem in the sample is provided in Appendix E. For the data base without prototypes, the lot which contained the prototypes was excluded. For some aircraft systems the prototypes were not easily recognisable in the lot data. When the prototypes appeared to be in the first lot, the first lot was excluded. For the data base with prototypes, the lots which had been excluded were added to the data base.

Learning Curve Effect. The data base in Appendix E was reviewed to determine which lots included the first 100 production aircraft airframes for each system. The results, which are listed in Appendix G, were used in the Hutchison learning curve software program to

determine the rate of learning, slope, the first unit cost of each system, and the tooling cost (in hours) of the first 100 airframes. For some of the systems, the Hutchison model would not provide the necessary information. Therefore, the learning curve formula was used to calculate the information for the following systems (32:23):

a. Data without prototypes: A-10, AV-8, C-141, F-15, and F-16.

b. Data with prototypes: A-6, C-141, F-18, S-3.

The slopes for each system for the data both with and without the prototypes are listed in Appendix H. The median slope for the data without prototypes was 69.13. The coefficient (b) for the quantity variable was ln .6913/ln 2 or -0.5326. The median slope for the data with prototypes was 62.07. The quantity coefficient for this data base was ln .6207/ln 2 or -0.6880. This information will be used later when the learning curve effect is incorporated into the model.

The cumulative average tooling hours (in thousands) for the first 100 airframes for each aircraft system were used as the dependent variable in the following regression analysis. Since the tooling hours are based on proprietary data they are not listed in this document.

<u>Logarithm-linear Regression.</u> Cumulative average tooling hours were regressed against various combinations of the independent variables aircraft unit weight, wing area, speed, and thrust-to-weight ratio. Using the criteria described in Chapter III, the single independent variable model which best fit the data without the prototypes was:

cumulative average tooling hours = f(aircraft unit weight)

$$Y = .0268 \times AUW^{.7111} \tag{13}$$

F-value: 18.123 F-table value: 3.05

t-value: AUW 4.257 t-table value: 1.071

Root MSE: .7679

Bringing the independent variable speed into the model resulted in an insignificant coefficient for speed (t-value = .936).

The model of tooling as a function of wing area and speed had t-values that were significant, but the Root MSE was .8025, which is higher than the Root MSE for the model selected above.

The best model for the data base including prototypes was:

cumulative average tooling = f(aircraft unit weight, speed)

$$Y = .0021 \times AUW^{.5883} \times S^{.6390} \tag{14}$$

F-value: 8.816 F-table value: 2.07

t-value: AUW 3.759 t-table value: 1.074

S 1.883

Root MSE: .7199

The model of tooling as a function of aircraft unit weight, speed, and thrust-to-weght ratio has a similar Root MSE (.7167), but the F-value decreases to 6.296.

Linear-linear Regression. The best model for the data base without prototypes was (Appendix I):

cumulative average tooling = f(aircraft unit weight, speed, thrust-to-weight ratio)

$$Y = -23.3537 + .0011AUW + .0263S + 21.3992TWR \tag{15}$$

F-value: 29.967 F-table value: 2.53

t-value: AUW 8.942

S 1.388

TWR 1.391

CV: 53.7595

Both tooling = f(AUW,S) and tooling = f(AUW, TWR) have a higher F-value (41.405 and 44.431, respectively); however, the CVs are higher (55.4082 and 55.3933, respectively).

The best model for the data base with prototypes is (Appendix J):

cumulative average tooling = f(aircraft unit weight, speed)

$$Y = -4.8288 + .00103AUW + .0445S \tag{16}$$

F-value: 66.235 F-table value: 2.07

t-value: AUW 11.187 t-table value: 1.074

S 2.806

CV : 35.2404

When the variable thrust-to-weight ratio was regressed in the model it was insignificant (t = 0.917).

<u>Logarithm-linear versus Linear-linear.</u> The linear-linear relationship fits the data best; therefore the linear-linear models were selected for further diagnosis.

<u>Potential Outlier.</u> For the model without prototypes, the following systems are outlying observations with respect to X in the data set (leverage value > .44): AV-8 and C-5. The data set also has observations which are outlying with respect to Y (t-table value = 1.345): AV-8, C-5, C-141, F-16, and F-111. According to the Cookd test, the only system that is having a significant influence on the estimated regression coefficients is the C-5 (F-table value = .829). The results of the diagnosis are listed in Appendix K. A sensitivity check was performed by eliminating this observation from the data set to determine if the data fits the regression line better without the C-5. The best model without the C-5 was:

cumulative average tooling = f(aircraft unit weight, speed, thrust-to-weight ratio)

$$Y = -17.2223 + .00075AUW + .0378S + 12.1371TWR \quad (17)$$

F-value: 7.015 F-table value: 2.57

t-values: AUW 3.198 t-table value: 1.079

S 1.992

TWR 0.789

CV: 68.4480

No improvements were identified by eliminating the C-5 data point. The data did not fit the line as well. The CV increased and the F-value decreased. Also, the thrust-to-weight ratio become insignificant.

For the data set which includes the prototypes, the systems which are outliers with respect to X (leverage value > .33) are: B-1, and C-5. The systems which were outliers with respect to Y (t-table value = 1.341) The C-5 observation was also an outlier for the data set with the prototype data (F-table value = .726). The results are listed in Appendix L. The sensitivity check produced the following results:

cumulative average tooling = f(aircraft unit weight, speed)

$$Y = -5.4541 + .00083AUW + .0517S \quad (18)$$

F-value: 21.991 F-table value: 2.88

t-value: AUW 4.728 t-table value: 1.076

S 3.162

CV: 42.5754

Eliminating the C-5 observation did not improve the model.

<u>Air Force/Navy Indicator Variable:</u> Using the Air Force/Navy indicator variable in interaction terms with the other potential independent variables did not improve the models for either data sets (with or without the prototypes). No model could be identified that

satisfied the criteria. All the models had variables that were insignificant (t-value < t-table value).

Aircraft Type Indicator Variable. Using the indicator variable which differentiates the cargo and bomber aircraft from the fighter, attack, and trainer aircraft in interaction terms with the other potential independent variable, improved the linear-linear models for both data sets. The indicator variable was set to one for the cargo and bomber aircraft and to zero for the fighter, attack, and trainer aircraft. Therefore, the interaction term, indicator times speed, is equal to speed for cargos and bombers and equal to zero for the fighter, attack, and trainer aircraft. The best model for the data without prototypes was (Appendix M):

cumulative average tooling = f[aircraft unit weight, speed, thrust-to-weight ratio, indicator x *speed (INDS)*]

$$Y = -33.5138 + .0013AUW + .0409S + 18.7520TWR - .0457INDS \qquad (19)$$

F-value: 25.425 F-table value: 2.44

t-value: AUW 8.128 t-table value: 1.079

S 2.012

TWR 1.272

INDS -1.567

CV: 51.1664

The model states that given an aircraft unit weight and a thrust-to-weight ratio, an increase in speed slightly decreases the amount of tooling for cargo and bomber aircraft, since the speed coefficients then are aggregately negative. For larger aircraft (cargo and bombers, production tooling costs are essentially driven by weight and thrust to weight features.

The best model for the data with the prototype data was (Appendix N):

cumulative average tooling = f(aircraft unit weight, speed, indicator x speed)

$$Y = -13.0647 + .0011AUW + .0543S - .0309INDS \qquad (20)$$

F-value:	46.199	F-table value:	2.53
t-value:	AUW 8.863	t-table value:	1.076
	S 3.103		
	INDS -1.234		

CV: 34.6433

This model implies that given an aircraft unit weight, an increase in speed will increase the amount of required tooling much less for cargo and bomber aircraft than for fighter, attack, and trainer aircraft.

Summary. Since the models with the interaction terms with the indicator for aircraft system types meet all the criteria and have lower CV values than the linear-linear models selected above, they fit the data to the line best. Since the CVs are lower than the representative differences (RDs) for the DAPCA III model, these models are better able to estimate the amount of tooling for future aircraft airframes.

	DAPCA III (RD)	Linear-linear (CV)
Without Prototypes	62.00%	51.17%
With Prototypes	54.62%	34.64%

Learning Curve Adjustment. The linear-linear models selected will provide the cumulative average cost of the first 100 airframes. The amount of tooling required for other quantities can be obtained by calculating the first unit cost using the following formula:

$$A = \frac{Y}{100^{b}} \tag{21}$$

where

A = first unit cost (hours)
Y = cumulative average cost of first 100 airframes from Eqs (19) or (20) (adjusted to hours)
b = -0.5362 for the data without prototypes [Eq (19)] and -0.6880 for the data including prototypes [Eq (20)]
100^{b} = .0846 for the data without prototypes [Eq (19)] and .0421 for the data including prototypes [Eq (20)]

Use this first unit cost (A) and Eq (12) to determine the cumulative average hours for the number of airframes being estimated.

Alternative to Manufacturing Factor

When tooling was regressed against engineering (ENGR) and manufacturing (MFG) for the data set without prototypes, engineering was significant but manufacturing was not significant (Appendix O):

cumulative total tooling = f(engineering, manufacturing)

$$Y = 110.4863 + 1.2842ENGR + .0162MFG \tag{22}$$

F-value: 79.573 F-table value: 2.07

t-value: ENGR 7.057 t-table value: 1.074

MFG 0.421

CV: 26.2050

Manufacturing was significant when tooling was regressed against engineering and manufacturing for the data set with prototypes (Appendix P):

cumulative total tooling = f(engineering, manufacturing)

$$Y = 471.8331 + .6255ENGR + .1056\ MFG \tag{23}$$

F-value: 79.752 F-table value: 2.07

t-value: ENGR 5.981 t-table value: 1.074

MFG 2.804

CV: 25.1669

<u>Historical Simulation.</u> Since the number of observations was small, when the most recent six observations were removed, six observations from earlier models was added to the data set. The six observations, which were removed, were: A-6, B-1, F-15, F-16, F-18, and P-3. The six observations that were added are listed in Appendix Q, along with the CES lot data information. There was a significant change to the model for the data without the prototypes. Manufacturing was significant in this model with older aircraft. In fact, manufacturing hours are more significant than engineering hours here.

cumulative total tooling = f(engineering, manufacturing)

$$Y = -427.307 + .7087ENGR + .1519MFG \qquad (24)$$

F-value: 65.710 F-table value: 2.07

t-value: ENGR 4.151 t-table value: 1.074

MFG 4.327

CV: 30.9549

When the simulation was run for the data with the prototypes there was not a significant change, except that note again that manufacturing is more significant than engineering historically.

cumulative total tooling = f(engineering, manufacturing)

$$Y = 749.0991 + .4511ENGR + .1742MFG \qquad (25)$$

F-value: 87.537 F-table value: 2.07

t-value: ENGR 3.616 t-table value: 1.074

MFG 4.798

CV: 24.313

Summary. This analysis indicates that for estimates of airframe costs that do not include the effort for prototypes, there has been a change in the relationship between tooling hours and engineering and manufacturing hours. In the past, both engineering and manufacturing were significant explanatory variables for tooling. However, more recently only engineering is significant in predicting tooling needs.

The analysis also suggests that engineering and manufacturing are both significant over time in explaining tooling needs when predicting the requirements for airframe costs that include the effort for prototypes.

Application Examples

To demonstrate and review the recommended cost estimating equations, some tooling hour estimates are derived based on the characteristics of a fictional aircraft. The fictional aircraft is a cargo plane with airframe unit weight (AMPR weight in the DAPCA model) of 110,000 pounds. Its speed (maximum mission speed at altitude in knots) is 500 miles per hour. Its thrust to weight ratio (military static thrust of the engine at sea level in pounds, divided by airframe unit weight) is .42.

Example one. Estimate of the development tooling hours for 5 prototype aircraft airframes.

Method one. From Eq (16), ignoring the cargo characteristic, the cumulative average tooling hours through unit 100 would be in thousands of hours:

$$-4.829 + .00103(110{,}000) + .0445(500) = 130.721 \text{ or } 130{,}720 \text{ hours}$$

A more accurate estimate can be derived from Eq (20). It's presumably a more accurate estimate since its CV is slightly lower.

The cumulative average tooling hours through unit 100 would be in thousands of hours:

$$-13.0647 + .0011(110{,}000) + .0543(500) - .0309(500)$$
$$= 119.64 \text{ or } 119{,}640 \text{ hours}$$

To derive the estimate for the cumulative average tooling hours of the 5 prototypes use Eq (12) with X equal to 5 and A, b, and 100 raised to the power of b are given by Eq (21):

$$A = \frac{119{,}640}{.0421} = 2{,}843{,}650 \text{ hours}$$

$$\text{cumulative average tooling hours} = 2{,}843{,}650 \times 5^{-.688} = 939{,}690$$

So the tooling hour estimate for the 5 prototypes would be:

$$939{,}690 \times 5 = 4{,}698{,}450 \text{ hours}$$

Method two. Using estimates for the total engineering hours and total manufacturing hours for the 5 prototypes, a total tooling hour estimate for the 5 prototypes can be derived from Eq (23). Assume the manufacturing estimate is 10,800,000 hours and the engineering estimate is 5,400,000 hours. From Eq (23) the total cumulative tooling estimate is:

$$471{,}833 + .6255(5{,}400{,}000) + .1056(10{,}800{,}000) = 4{,}990{,}000 \text{ hours.}$$

Whether the estimate of method one or two is more reliable, depends on the reliability of the manufacturing and engineering hour estimates.

Example two. Assuming the same scenario as example one, to estimate the tooling hours for the first 80 production aircraft airframes, use one of the following methods.

Method one. From Eq (15), ignoring the cargo characteristic, cumulative average tooling hours through unit 100 would be in thousands of hours:

$$-23.3537 + .0011(110{,}000) + .0263(500) + 21.3992(.42) = 117.784$$
or 117,784 hours

A more accurate estimate is derived from Eq (19). Cumulative average tooling hours through unit 100 is:

$$-33.5138 + .0013(110{,}000) + .0409(500) + 18.7520(.42) - .0457(500)$$
$$= 114.962 \text{ or } 114{,}962 \text{ hours}$$

To determine the cumulative average tooling hours, use Eq (12) with X equal to 80 and A, b, and 100 raised to the power of b given by Eq (21):

$$A = \frac{114{,}962}{.0846} = 1{,}358{,}889$$

$$\text{cumulative average tooling hours} = 1{,}358{,}889 \times 80^{-.5362} = 129{,}642$$

The tooling hour estimate for the first 80 airframes would be:

$129{,}642 \times 80 = 10{,}371{,}360$ hours

Method two. *Using estimates for* the total engineering hours ad the total manufacturing hours, an estimate of the total tooling hours for the 80 production airframes can be derived using Eq (22). Assume the total engineering hours estimate was 12,000,000 and the total manufacturing hours estimate was 24,000,000 for the 80 airframes. Using Eq (22) the total tooling hours would be:

$$471.8331 + .6255(12{,}000{,}000) + .1056(24{,}000{,}000)$$
$$= 10{,}040{,}871 \text{ hours}$$

Method three. If an accurate (error smaller than 10 percent) total prototype cost estimate is also available, use the technique of example one to derive total cost of development plus production of the first 80 aircraft. Then subtract the prototype cost. In this scenario, this method would be preferred, since the estimating error of the equations with prototypes is smaller than the estimating error of the equations without prototypes.

V. Conclusions/Recommendations

Conclusions

Budget constraints have placed an increased emphasis on the accuracy of DoD weapon system cost estimates. The DAPCA III model is often used by Air Force personnel to estimate the tooling costs of aircraft airframes. This study evaluates the accuracy, independent variables, and data base of the DAPCA III model, and then provides alternative models for estimating tooling for airframes.

Accuracy of DAPCA III. To determine the accuracy of the DAPCA III model in estimating aircraft airframe tooling costs, the representative difference was calculated for the data set both with and without prototypes. The representative differences for the data with and without prototypes, were 62.00 and 54.62 percent, respectively.

DAPCA III Independent Variables. The independent variables were reviewed to determine if they are still logical variables for estimating tooling costs of future aircraft airframes. Airframe unit weight appears to be a good variable to explain the size of the airframe. The variable speed captures the variations due to performance. The performance characteristic thrust-to-weight ratio was not used in DAPCA III but should capture variations due to maneuverability of the aircraft systems.

DAPCA III does not have a variable for changes in production rate, technology, or complexity. Careful consideration of each of these factors indicated that they are difficult to quantify . Therefore, it is logical that they were not included in DAPCA III.

There are not any indicator variables in DAPCA III. Other studies have shown that indicator variables for aircraft type or DoD service component (Air Force versus Navy) have been significant.

The method used to account for the learning effect for various quantities of airframes was considered appropriate.

Overall, the variables used in DAPCA III seem logical; however, there was a possibility that other variables might also be significant. These variables include: wing area, thrust-to-weight ratio, and indicator variables.

DAPCA III Data Base. The data base used in DAPCA III was updated to include more current aircraft systems.

Alternative Models. Although Rand found that the logarithm-linear form fit the data best, the best models found in this study had a linear-linear form. Models were developed using the data both with and without the prototypes included [Eqs (18) and (19)].

For both models, an indicator variable for aircraft type was significant when used in an interaction term with speed. This indicates that changes in speed impact tooling differently for cargo and bombers than for fighter, attack, and trainer aircraft. An analysis with indicator variables for Air Force versus Navy did not improve the models.

This study indicates that Eqs (18) and (19) are more accurate than DAPCA III (51.17 and 34.64 percent, respectively).

Alternative to Manufacturing Factor. When tooling is regressed against engineering and manufacturing the relationship between the variables becomes apparent. For the data without the prototypes only engineering is significant. Both engineering and manufacturing are

significant for the data including the prototypes. In the past manufacturing was more significant for both data sets. This suggests that engineering drives the amount of tooling more than manufacturing.

Recommendations for Further Research

1. In light of the findings in this study, the other equations in DAPCA III should be updated.

2. Several assumptions were needed to identify which lot data in the CES contained prototype data. Since this study indicates that results differ depending on whether prototype data is included, the data should be updated to clearly indicate prototypes.

3. The method used to adjust for the learning curve effort is adequate but cumbersome. It also leads to estimating error compounding (the estimating error of the cost estimating model combined with the estimating error of the learning curve). Alternate techniques to handle the learning effect should be studied.

Appendix A: Comparison of DAPCA Data

DAPCA I	DAPCA II	DAPCA III
A-3J	A-3	A-3
B-52	A-4	A-4
B-58	A-5	A-5
B-66	A-7A	A-6
F-3H	A-7B	A-7
F-84	B-47	B-52
F-84F	B-52	B-58
F-86	B-58	RB-66
F-86D	B-66	F-3
F-89	F-3	F-4
F-100	F-4	F-6
F-101	F-84	F-14
F-102	F-84F	F-100
F-104	F-86	F-102
F-105	F-86D	F-104
F-106	F-89	F-105
T-38	F-100	F-106
	F-101	F-111
	F-102	T-38
	F-104	T-39
	F-105	C-5
	F-106	C-130
	F-111	C-133
	C-124	C-141
	C-130	KC-135
	C-133	
	C-141	
	KC-135	
	OV-10	

Appendix B: Input Data for DAPCA III

MODEL	AMPR WT	SPEED	QUANTITY
A-3	23104	544	50
A-4	4987	545	165
A-5	22900	1147	25
A-6	17176	530	473
A-7	11522	595	199
B-52	133056	551	195
B-58	32400	1147	116
B-66	28551	548	59
F-3	10400	460	265
F-4	18100	1283	540
F-6	8845	581	419
F-14	26500	1170	577
F-100	14087	775	1274
F-102	12000	680	847
F-104	8170	1150	230
F-105	17954	1192	610
F-106	14630	1153	277
F-111	32926	1262	235
T-38	5350	699	492
T-39	7027	468	149
C-5	279145	480	76
C-130	43431	315	231
C-133	97610	302	15
C-141	104300	491	279
KC-135	70378	527	426

Appendix C: DAPCA III Representative Difference (without prototypes)

MODEL	DIFFERENCE	$(\text{DIFFERENCE})^2$
A-3	693.1	480,387.6
A-4	-1,861.3	3,464,437.7
A-5	3,619.7	13,102,228.1
A-6	2,705.3	7,318,648.1
A-7	3,137.5	9,843,906.3
B-52	13,257.6	175,763,957.8
B-58	-7,390.6	54,620,968.4
B-66	4,106.2	16,860,878.4
F-3	1,874.1	3,512,250.8
F-4	8,964.1	80,355,088.8
F-6	-6,619.6	43,819,104.2
F-14	-551.9	304,593.6
F-100	806.4	650,281.0
F-102	1,211.6	1,467,974.6
F-104	2,955.1	8,732,616.0
F-105	6,318.7	39,925,969.7
F-106	1,455.6	2,118,771.4
F-111	-5,414.0	29,311,396.0
T-38	-153.4	23,531.6
T-39	1,070.2	1,145,328.0
C-5	2,774.3	7,696,740.5
C-130	-1,144.2	1,309,193.6
C-133	6,257.0	39,150,049.0
C-141	11,603.2	134,634,250.2
KC-135	-1,884.9	3,552,848.0

Appendix D: DAPCA III Representative Difference (with prototypes)

MODEL	DIFFERENCE	$(\text{DIFFERENCE})^2$
A-3	231.1	53,407.2
A-4	-2,021.0	4,084,441.0
A-5	3,619.7	13,102,228.1
A-6	923.8	853,406.4
A-7	3,137.5	9,843,906.3
B-52	13,257.6	175,763,957.8
B-58	-7,390.6	54,620,968.4
B-66	4,106.2	16,860,878.4
F-3	1,658.7	2,751,285.7
F-4	8,964.1	80,355,088.8
F-6	-6,880.1	47,335,776.0
F-14	-6,428.9	41,330,755.2
F-100	806.4	650,281.0
F-102	-6,403.8	41,008,654.4
F-104	2,955.1	8,732,616.0
F-105	6,318.7	39,925,969.7
F-106	1,455.6	2,118,771.4
F-111	-5,414.0	29,311,396.0
T-38	-799.2	638,401.0
T-39	1,070.2	1,145,328.0
C-5	-396.4	157,133.0
C-130	-3,190.8	10,181,204.6
C-133	6,189.8	38,313,624.0
C-141	6,691.8	44,780,187.2
KC-135	-2,437.9	5,943,356.4

Appendix E: CES Lot Data Information for Model Analysis

MODEL	WITHOUT PROTOTYPES	WITH PROTOTYPES
A-4 (page 4-39)	A4D-1(A-4A): lot qty 9, 10, 52, 94	Add: XA4D-1, lot qty 1
A-6 (page 4-97)	A-6A: lot qty 12, 23, 37, 48, 64, 112, 63, 78, 36	Add: A-6A, lot qty 8 Page 4-85 reports 8 developmental aircraft were made.
A-7 (page 4-147)	A-7A: lot qty 199 A-7B: lot qty 196	Assumed prototypes included in lot of 199.
A-10 (page 4-176)	A-10A: lot qty 6, 22, 30, 43, 100, 144, 144, 20	Add: YA-10A, lot qty 2
AV-8 (page 4-199)	AV-8B: lot qty 4, 12, 18	Cost data for 2 prototypes (YAV-8B) were not available.
B-1 (page 4-214)	B-1B: lot qty 1, 7, 10	Assumed prototypes contained in first lot of B-1B. Add: lot qty 4

MODEL	WITHOUT PROTOTYPES	WITH PROTOTYPES
C-5 (page 4-297)	C-5A: lot qty 8 18 27 23	Assumed prototypes contained in first lot of C-5A. Add: lot qty 5
C-141 (page 4-345)	C-141A: lot qty 145 134	Assumed prototypes contained in first lot of C-141A. Add: lot qty 5
E-2 (page 4-362)	E-2C: lot qty 11 8 9 6 6 11 6 6 6 10	Assumed first lot of E-2C contained prototypes. Add: lot qty 2
F-5 (page 4-482)	F-5E: lot qty 21 16 214 57 40 55 48 12	Assumed first lot of F-5E contained prototypes. Add: lot qty 5
F-14 (page 4-513)	F-14A: lot qty 26 48 48 50 30 50 50 36 45 44 36 30 30 30 24	Assumed first 2 lots of F-14A were prototypes. Add: lot qty 6 6

MODEL	WITHOUT PROTOTYPES	WITH PROTOTYPES
F-15 (page 4-544)	F-15A/B: lot qty 20, 30, 62, 72, 132, 21, 108	Assumed prototypes included in lot of 20.
F-16 (page 4-575)	F-16A/B: lot qty 55, 105, 145, 75, 348, 175, 180, 160	Assumed first lot of F-16A/B contained prototypes. Add: lot qty 8
F-18 (page 4-599)	F/A-18A: lot qty 9, 25, 60, 63, 18, 17, 84, 84	Assumed first lot of F-18A contained prototypes. Add: lot qty 11
F-111 (page 4-798)	F-111A: lot qty 18, 141, 76	Assumed prototypes included in lot of 18.

MODEL	WITHOUT PROTOTYPES	WITH PROTOTYPES
P-3 (page 4-845)	P-3C: lot qty 24, 23, 24, 12, 24, 12, 12, 12, 11, 15, 10, 14, 12, 12, 3, 12, 4, 12, 4, 6, 3, 5	Assumed prototypes included in lot of 24.
S-3 (page 4-881)	S-3A: lot qty 13, 35, 45, 45, 41	Assumed first lot of S-3A contains prototypes. Add: lot qty 8
T-38 (page 4-898)	T-38A: lot qty 4, 13, 50, 144, 144, 137	Add: YT-38, lot qty 2

Appendix F: Alternative Model Independent Variables

MODEL	AIRFRAME UNIT WEIGHT	WING AREA	SPEED	THRUST-TO-WEIGHT RATIO
A-4	4,987	260.0	545	1.4036
A-6	17,176	528.8	530	0.4949
A-7	11,522	375.0	595	0.9851
A-10	14,842	506.0	423	0.5383
AV-8	7,662	230.0	486	2.1480
B-1	146,717	1950.0	1518	0.0891
C-5	279,145	6200.0	480	0.1462
C-141	104,300	3228.1	491	0.1822
E-2	22,800	700.0	302	0.1916
F-5	7,180	186.0	940	0.4875
F-14	26,500	565.1	1170	0.4660
F-15	17,642	608.0	1434	0.8148
F-16	10,104	300.0	1265	1.4519
F-18	16,070	400.0	990	0.6601
F-111	32,926	525.0	1262	0.3265
P-3	44,532	1300.0	382	0.1051
S-3	19,248	598.0	393	0.3600
T-38	5,350	170.0	699	0.5009

Appendix G: CES Lot Data Information for Learning Curves

MODEL	WITHOUT PROTOTYPES	WITH PROTOTYPES
A-4 (page 4-39)	A4D-1: lot qty 9, 10, 52, 94	Add: XA4D-1, lot qty 1
A-6 (page 4-97)	A-6A: lot qty 12, 23, 37, 48	Add: A-6A, lot qty 8
A-7 (page 4-147)	A-7A: lot qty 199 A-7B: lot qty 196	No change.
A-10 (page 4-176)	A-10A: lot qty 6, 22, 30, 43	Add: YA-10A, lot qty 2
AV-8 (page 4-199)	AV-8B: lot qty 4, 12, 18	No change.
B-1 (page 4-214)	B-1B: lot qty 1, 7, 10	Add: B-1B, lot qty 4
C-5 (page 4-297)	C-5A: lot qty 8, 18, 27, 23	Add: C-5A, lot qty 5
C-141 (page 4-345)	C-141A: lot qty 145, 134	Add: C-141A, lot qty 5

MODEL	WITHOUT PROTOTYPES	WITH PROTOTYPES
E-2 (page 4-362)	E-2C: lot qty 11, 8, 9, 6, 6, 11, 6, 6, 6, 10	Add: E-2C, lot qty 2
F-5 (page 4-482)	F-5E: lot qty 21, 16, 214	Add: F-5E, lot qty 5
F-14 (page 4-513)	F-14A: lot qty 26, 48, 48	Add: F-14A, lot qty 6, 6
F-15 (page 4-544)	F-15A/B: lot qty 20, 30, 62	No change.
F-16 (page 4-575)	F-16A/B: lot qty 55, 105	Add: F-16A/B, lot qty 8
F-18 (page 4-599)	F/A-18A: lot qty 9, 25, 60, 63	Add: F/A-18A, lot qty 11
F-111 (page 4-798)	F-111A: lot qty 18, 141	No change.
P-3 (page 4-845)	P-3C: lot qty 24, 23, 24, 12, 24	No change.
S-3 (page 4-881)	S-3A: lot qty 13, 35, 45, 45	Add: S-3A, lot qty 8

MODEL	WITHOUT PROTOTYPES	WITH PROTOTYPES
T-38 (page 4-898)	T-38A: lot qty 4 13 50 144	Add: YT-38, lot qty 2

Appendix H: Learning Curve Data

MODEL	WITHOUT PROTOTYPES SLOPE	WITH PROTOTYPES SLOPE
A-4	69.97	71.32
A-6	64.92	60.07
A-7	86.64	86.64
AV-8	63.46	63.46
A-10	57.02	68.20
B-1	80.03	65.00
C-5	69.63	76.96
C-141	59.25	59.30
E-2	81.41	81.41
F-5	65.85	60.67
F-14	83.40	59.99
F-15	57.16	57.16
F-16	143.91	58.57
F-18	67.51	58.99
F-111	68.93	68.93
P-3	78.06	78.06
S-3	69.33	58.40
T-38	60.55	60.27

Appendix I: Linear-Linear Model SAS Output (without prototypes)

Tooling = f(AUW, S, TWR)

ANALYSIS OF VARIANCES

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	3	88837.08095	29612.36032	29.967	0.0001
ERROR	14	13834.36495	988.16893		
C TOTAL	17	102671.44590			

ROOT MSE	31.43515	R-SQUARE	0.8653
DEP MEAN	58.47369	ADJ R-SQ	0.8364
C.V.	53.75949		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	-23.3537	20.83122	-1.121	0.2811
AUW	1	0.0011	0.00012	8.942	0.0001
S	1	0.0263	0.01898	1.388	0.1869
TWR	1	21.3992	15.38684	1.391	0.1860

VARIABLE	N	MEAN	STD DEV	SUM	MINIMUM	MAXIMUM
TOOL	18	58.47	77.71	1052.5	5.582	321.3
AUW	18	43816.83	69413.94	788703.0	4987.000	279145.0
S	18	772.50	401.71	13905.0	302.000	518.0
TWR	18	0.63	0.55	11.4	0.089	2.1

Appendix J: Linear-Linear Model SAS Output (with prototypes)

Tooling = f(AUW, S)

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	2	91523.29255	45761.64628	66.235	0.0001
ERROR	15	10363.53837	690.90256		
C TOTAL	17	101886.83092			

ROOT MSE	26.28503	R-SQUARE	0.8983
DEP MEAN	74.58769	ADJ R-SQ	0.8847
C.V.	35.24043		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	-4.82883	14.34419	-0.337	0.7411
AUW	1	0.00103	0.00009	11.187	0.0001
S	1	0.04453	0.01587	2.806	0.0133

VARIABLE	N	MEAN	STD DEV	SUM	MINIMUM	MAXIMUM
TOOL	18	74.59	77.42	1342.6	5.582	320.2
AUW	18	43816.83	69413.94	788703.0	4987.000	279145.0
S	18	772.50	401.71	13905.0	302.000	1518.0

Appendix K: Outlier Diagnostic Data (without prototypes)

MODEL	LEVERAGE	STUDENTIZED DELETED RESIDUAL	COOK'S D
A-4	0.1917	-0.3353	0.0071
A-6	0.0979	-0.0429	0.0001
A-7	0.0943	-0.6695	0.0122
A-10	0.1191	0.3007	0.0032
AV-8	0.5690	1.4577	0.6491
B-1	0.3995	-1.0178	0.1718
C-5	0.7897	1.7209	2.4382
C-141	0.1411	-1.5953	0.0941
E-2	0.2026	1.0066	0.0642
F-5	0.1002	-0.3132	0.0029
F-14	0.1297	-0.2317	0.0022
F-15	0.2242	0.8195	0.0497
F-16	0.2719	-1.5710	0.2036
F-18	0.0833	-1.3493	0.0030
F-111	0.1740	3.4378	0.3512
P-3	0.1746	-0.8483	0.0388
S-3	0.1449	0.2637	0.0032
T-38	0.0923	-0.0553	0.0001

Appendix L: <u>Outlier Diagnostic Data (with prototypes)</u>

MODEL	LEVERAGE	STUDENTIZED DELETED RESIDUAL	COOK'S D
A-4	0.0932	-0.2531	0.0023
A-6	0.0859	0.0057	0.0000
A-7	0.0800	-1.1166	0.0356
A-10	0.1107	-0.2895	0.0037
AV-8	0.1018	2.1498	0.1407
B-1	0.3903	-1.0399	0.2295
C-5	0.7603	1.3445	1.8138
C-141	0.1285	-0.7093	0.0256
E-2	0.1420	0.3937	0.0091
F-5	0.0819	-0.8797	0.0234
F-14	0.1166	0.9118	0.0370
F-15	0.2228	-0.1257	0.0016
F-16	0.1572	-1.0794	0.0717
F-18	0.0820	0.6794	0.0143
F-111	0.1442	1.8369	0.1636
P-3	0.1111	-1.9684	0.1355
S-3	0.1158	0.6952	0.0219
T-38	0.0757	0.1062	0.0003

Appendix M: Alternative Model SAS Output (without prototypes)

Tooling = f(AUW, S, TWR, INDS)

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	4	91034.63501	22758.65875	25.425	0.0001
ERROR	13	11636.81089	895.13930		
C TOTAL	17	102671.44590			

ROOT MSE	29.91888	R-SQUARE	0.8867
DEP MEAN	58.47369	ADJ R-SQ	0.8518
C.V.	51.1664		

PARAMETER ESTIMATES

VARIABLE	DF	ESTIMATE	ERROR	PARAMETER=0	PROB > |T|
INTERCEP	1	-33.5138	20.85989	-1.607	0.1321
AUW	1	0.0013	0.00015	8.128	0.0001
S	1	0.0409	0.02031	2.012	0.0654
TWR	1	18.7520	14.74179	1.272	0.2256
INDS	1	-0.0457	0.02916	-1.567	0.1412

Appendix N: Alternative Model SAS Output (with prototypes)

Tooling = f(AUW, S, INDS)

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	3	92539.21210	30846.40403	46.199	0.0001
ERROR	14	9347.61883	667.68706		
C TOTAL	17	101886.83092			

ROOT MSE	25.83964	R-SQUARE	0.9083
DEP MEAN	74.58769	ADJ R-SQ	0.8886
C.V.	34.64330		

PARAMETER ESTIMATES

VARIABLE	DF	ESTIMATE	ERROR	PARAMETER=0	PROB > |T|
INTERCEP	1	-13.0647	15.60196	-0.837	0.4164
AUW	1	0.0011	0.00013	8.863	0.0001
S	1	0.0543	0.01750	3.103	0.0078
INDS	1	-0.0309	0.02502	-1.234	0.2377

Appendix O: TOOL/ENGR/MFG Model SAS Output (without prototypes)

Tooling = f(ENGR, MFG)

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	2	689411923.72	344705961.86	79.573	0.0001
ERROR	15	64979000.78	4331933.39		
C TOTAL	17	754390924.50			

ROOT MSE	2081.33	R-SQUARE	0.9139
DEP MEAN	7942.50	ADJ R-SQ	0.9024
C.V.	26.20497		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	110.4863	875.6260	0.126	0.9013
ENGR	1	1.2842	0.1820	7.057	0.0001
MFG	1	0.0162	0.0384	0.421	0.6795

VARIABLE	N	MEAN	STD DEV	SUM	MINIMUM	MAXIMUM
TOOL	18	7942.50	6661.53	142965.0	2090.00	25399.00
ENGR	18	5693.89	4727.68	102490.0	782.00	19226.00
MFG	18	32190.00	22432.06	579420.0	4407.00	74562.00

Appendix P: TOOL/ENGR/MFG Model SAS Output (with prototypes)

Tooling = f(ENGR, MFG)

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	2	1026713347	513356673.41	79.752	0.0001
ERROR	15	96553227	6436911.13		
C TOTAL	17	1123267014			

ROOT MSE	2537.107	R-SQUARE	0.9140
DEP MEAN	10081.110	ADJ R-SQ	0.9026
C.V.	25.16694		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	471.8331	1057.9623	0.446	0.6620
ENGR	1	0.6255	0.1046	5.981	0.0001
MFG	1	0.1056	0.0377	2.804	0.0134

VARIABLE	N	MEAN	STD DEV	SUM	MINIMUM	MAXIMUM
TOOL	18	10081.11	8128.62	181460.0	2090.0	28911.0
ENGR	18	9412.06	8952.00	169417.0	782.0	33599.0
MFG	18	35257.39	24863.01	634633.0	4407.0	88767.0

Appendix Q: CES Lot Data Information for Historical Simulation

MODEL	WITHOUT PROTOTYPES	WITH PROTOTYPES
A-5 (page 4-73)	A-5A: lot qty 11, 14	Assumed prototypes included in lot of 11.
B-58 (page 4-265)	B-58A: lot qty 17, 36, 20, 30	Add: B-58A, lot qty 13
F-4 (page 4-411)	F-4A: lot qty 16, 24	Add: F-4A, lot qty 7
F-104 (page 4-734)	F-104A: lot qty 17 F-104B: lot qty 6 F-104A/C: lot qty 209 F-104C: lot qty 21	Add: XF-104A, lot qty 2
F-105 (page 4-752)	F-105B: lot qty 65	Add: YF-105A/B, lot qty 15
KC-135 (page 4-824)	KC-135A: lot qty 29, 68, 118, 130, 81	Add: KC-135, lot qty 1

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The purpose of this study was to evaluate the tooling cost estimating equation of the DAPCA III model and determine if more accurate models can be developed. The five objectives of the research were: (1) Determine the accuracy of the DAPCA III model. (2) Determine if the independent variables in DAPCA III are logically valid. (3) Determine if the data base which was used to develop DAPCA III is appropriate for estimating today's aircraft systems. (4) Determine if the accuracy of the DAPCA III model can be improved. (5) Determine if using a factor of manufacturing is sufficient to estimate tooling costs.

The study found that the accuracy of the DAPCA III model can be improved by including additional variables and updating the data base. More accurate models were developed for the data base both including and excluding the prototype aircraft systems.

When tooling was regressed against manufacturing and engineering, the data without the prototypes indicated that engineering was more significant than manufacturing. Both manufacturing and engineering were significant for the data with the prototypes. Key words.